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A New Pre-Distorter for Linearising Power Amplifiers using Genetic Algorithm

BIPIN P. R[1], P.V. RAO[2]
[1]Research Scholar, VTU Belgaum, India,
[2]Professor, Vignana Bharathi Institute of Technology, Hyderabad, TS, India.

Abstract: The High Power Amplifier(HPA) has, of late, surfaced as an essential element for any type of wireless communication systems. To get superior energy-efficiency, the HPA is expected to function at the saturation level, leading to the generation of the non linear outputs. For the purpose of averting the non-linearization in HPA, a pre-distorter is appropriately devised and placed in front of the HPA. In this paper, an innovative pre-distorter is devised by employing Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) optimization algorithms. The pre-distorter is built up by means of a memory wiener HPA model. The new approach is performed in the working platform of the MATLAB and the outputs achieved are assessed and appraised. The pre-distortion using GA has produced better results in terms of MSE compared to that produced using PSO.

Keywords: Digital Predistorter, Particle Swarm Optimization, Genetic Algorithm, Wiener Model

I. INTRODUCTION

Powers amplifiers (PAs) are designed to raise up the power level of the signal before transmitting it to the antenna. They also shows the memory effects [1], which is undesirable. Further, they tend to be invariably nonlinear. The amplifiers which are incredibly linear with superb effectiveness have become a rare specimen. The Pre-distorter recompenses for the nonlinear distortion envisaged by the PA by working on the input signal. The theory of the digital pre-distorter (DPD) is easy to comprehend. Here, a nonlinear distortion function is generated within the digital horizon which represents the inverse of the amplifier function [2]. The DPD will be connected in front of the PA. In fact, it is very easy to realize an incredibly linear and inferior distortion system in principle, by blending the two nonlinear systems (DPD and PA) in series. The process followed in this paper offer the pre-distortion before the power amplifier with the help of the optimization method to achieve linearity in the combined system. The PA is modelled using Wiener model and the pre-distorter is designed using Hammerstein model. At the output of wiener HPA model, the authentic constraint vector is achieved and it is optimized by means of optimization approaches [3] such as Particle swarm optimization (PSO) [4] and Genetic Algorithm (GA). In SectionII, a brief account of the wiener HPA model and basics of PSO and GA are given which is used for the optimization of Wiener HPA results to devise a pre-distorter. SectionIII describes the predistorter design. The test outcomes and consequential appraisal are presented in SectionIV. Finally, the conclusions are effectively exhibited in SectionV.

II. POWER AMPLIFIER MODEL

Most commonly used power amplifier model is wiener model which incorporates a memoryless nonlinearity preceded by a linear filter[2]. The inverse of wiener model can be easily implemented by using Hammerstein model (a linear filter preceded by a memoryless nonlinearity). The memory effect of power amplifier can be represent by linear filter of order K_l and is represented by [1]

$$H(z) = \sum_{i=0}^{K_l} h_i z^{-i} \quad (1)$$

Where, the linear filter coefficient vector can be represented by

$$h = [h_0\, h_1\, \dots h_{K_l}]^T \quad (2)$$

The PA provides amplitude and phase distortion to the input signal applied to it [5] and this can be considered as the traveling wave tube (TWT) nonlinearity. Let x(k) be the input signal applied to the memory power amplifier, then the output from linear filter can be given by

$$w(k) = \sum_{i=0}^{k_l} h_i x(k-i) \quad (3)$$

Which is the input to the TWT nonlinearity and the distorted output from the wiener model can be denoted as:

$$y(k) = A(e_w(k)).\exp\Big(j\big(\psi(k) + \phi(e_w(k))\big)\Big) \quad 4)$$

Where $e_w(k)$ and $\phi(e_w(k))$ indicates the amplitude and the phase of the complex signal w(k) respectively, also $A(e_w(k))$ and $\psi(k)$ defines the amplitude distortion and phase distortion produced by the nonlinearity respectively. The expression for the nonlinearity is given below:

$$A(e) = \begin{cases} \frac{\alpha_a e}{1+\beta_a e^2}, & 0 \le e \le e_{sat} \\ A_{max}, & e > e_{sat} \end{cases} \quad (5)$$

$$\phi(e) = \frac{\alpha_{\emptyset} e^2}{1+\beta_{\emptyset} e^2} \quad (6)$$

In above equation $t = [\alpha_a\ \beta_a\ \alpha_{\emptyset}\ \beta_{\emptyset}]^T$ gives the parameter vector for TWT nonlinearity [6], e is the amplitude of input given to memory less nonlinearity, e_{sat} is the saturating input and A_{max} is the output saturation amplitude. The expression for input and output saturation can be represented as:

$$e_{sat} = \frac{1}{\sqrt{\beta_a}} \quad (7)$$

$$A_{max} = \frac{\alpha_a}{2\sqrt{\beta_a}} \quad (8)$$

The wiener power amplifier's linear filter coefficients and nonlinearity coefficients are assigned with typical values [1] as h^T= [0.7692 0.1538 0.0769] and t^T= [2.1587 1.15 4.0 2.1].

A. Wiener Model Identification

For the identification purpose a normalized 64-QAM signal was generated [2]. The generated QAM signal was applied to wiener model to create training data set {x(k),y(k)}, where x(k) is the input QAM and y(k) is output from the model, the diagram is shown in fig.1. The true parameter of memory high power amplifier is estimated using the training data. The true parameter vector is defined as:

$$\alpha = [\alpha_1\ \alpha_2\ \ldots\ \alpha_{N_\alpha}]^T \quad (9)$$

where N_α represents the total number of parameter to be estimated, that is the sum of number of linear filter coefficients and number of nonlinearity coefficients.

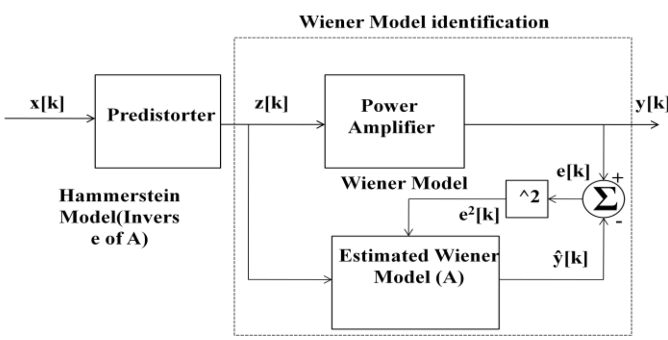

Fig 1. Wiener Model Identification and Predistorter Design.

The training data input x(k) is applied to the model and measured output y(k) usually is corrupted by the small noise .The output from the estimated wiener model is denoted by ŷ(k). The error results between the desired output y(k) and the model output ŷ(k) is e(k)=y(k)- ŷ(k), thus mean square error cost function can be given by

$$J(\tilde{\alpha}) = \frac{1}{K}\sum_{k=1}^{K}|e(k)|^2 \quad (10)$$

The true parameter vector α is estimated by finding the solution of the following optimization problem

$$\hat{\alpha} = \arg\min_{\hat{\alpha}\in\emptyset} J(\tilde{\alpha}) \quad (11)$$

Where the search space is given as

$$\emptyset \triangleq \prod_{i=1}^{N_\alpha}[\alpha_{i,min} \quad \alpha_{i,max}] \quad (12)$$

The true parameter α is an element of the search space. The cost function (10) is a nonlinear function and has local minima. The above challenging identification problem is solved here using PSO and GA algorithms.

B. PSO

For solving the optimization problem (11) to find a solution $\hat{\alpha}$ using PSO algorithm the swarm size (S), number of iterations (L_{max}) and the search space( ) are needed to be determined.Eachswarmposition $\tilde{\alpha}(m) = [\tilde{\alpha}_1(m)\ \tilde{\alpha}_2(m)\ \ldots\tilde{\alpha}_{N_\alpha}(m)]^T$ has N_α–dimensional velocity $v(m) = [v_1(m)\ v_2(m) \ldots v_{N_\alpha}(m)]^T$ to direct its search, and with the velocity space is given as

$$V \triangleq \prod_{i=1}^{N_\alpha}[-v_{i,max} \quad v_{i,max}] \quad (13)$$

Where,$v_{i,max} = (1/2)[\alpha_{i,max} - \alpha_{i,min}]$.

At the beginning of PSO, the particles are initialized randomly within search space, and the velocity for each particle is initialized to zero . The cognitive information $pb^l(m)$ (personal best) and the social information gb^l (global best) record the best position visited by the particle m and the best position visited by the entire swarm, respectively, during the l movements. The MSE costs associated with $pb^l(m)$ and gb^l are given by $J(pb^l(m))$ and $J(gb^l)$, respectively. Using $pb^l(m)$ and g^l the velocities and positions are updated according to,

$$v^{l+1}(m) = I_\omega \cdot v^l(m) + rand \cdot c_1 \cdot \left(pb^l(m) - \tilde{\alpha}^l(m)\right) + rand \cdot c_2 .\ (gb^l - \tilde{\alpha}^l(m)) \quad (14)$$

$$\tilde{\alpha}^{l+1}(m) = \tilde{\alpha}^l(m) + v^{l+1}(m) \quad (15)$$

Where I_ω indicates the inertia weight, rand is the random number uniformly distributed in [0, 1], c_1 and c_2 are the two acceleration coefficients. To obtain improved results we take $I_\omega = rand$ instead of a constant inertia weight [4]. The time varying acceleration coefficients were chosen as which can often enhance the performance of PSO ([4]-[8]) in which.

$$c_1 = 2.5 - (2.5 - 0.5) \cdot {}^{l}/_{L_{max}},$$

$$c_2 = 0.5 + (2.5 - 0.5) \cdot {}^{l}/_{L_{max}}, \quad (16)$$

The implementation of the wiener power amplifier model was carried out with linear filter coefficients h^T=[0.7692 0.1538 0.0769] and nonlinearity coefficients t^T=[2.1587 1.15 4.0 2.1]. Swarm size will be set to 20 and the number of iterations and L_{max}=80. In this work in order to preserve the model characteristics search space is reduced. That is the upper and lower limits are selected to be [0.8, 0.2, 0.1, 2.3, 1.3, 4.2, 2.2] and [0.6 0.1 0.0 2.0 1.1 3.8 1.9] respectively

C. Genetic Algorithm (GA)

The Genetic Algorithm represents an adaptive global search technique in accordance with the evolutionary data of genetics. For the purpose of solving the optimization challenges the Genetic Algorithm is effectively utilized as an arbitrary search technique. In the GA, the Iterations are represented as the generation of modernized solutions and the population is characterized as the chromosomes. The number of solution or hidden neuron is set to the 20. Total number of iteration is made equal to 100. Upper bound (Ub) is set to [0.8 0.2 0.1 2.3 1.3 4.2 2.2] and Lower bound (lb) is set to [0.6 0.1 0.0 2.0 1.1 3.8 1.9]

III. PREDISTORTER DESIGN

The predistorter is implemented using Hammerstein model as it represents the inverse form of the wiener model. The linear filter of Hammerstein model is made to be inverse of linear filter of identified wiener power amplifier model and inverse nonlinearity of estimated wiener is used to implement the Hammerstein nonlinearity.

Consider the transfer function of the Hammerstein Predistorter's linear filter

$$Q(z) = z^{-\tau} \sum_{i=0}^{N_h} q_i z^{-i} \quad (17)$$

Where q_i represents the linear filter coefficient and τ is the delay. If H(z) is the transfer function of linear filter of wiener model and is a minimum phase filter then τ=0. The filter coefficient of predistorter can be obtained by solving the linear equations derived from

$$Q(z).H(z) = z^{-\tau} \quad (18)$$

Let e denotes the amplitude of the input signal x(k). Consider the amplitude gain function of the predistorter's nonlinearity is P(e) and the corresponding phase predistortion function by Ω(e). From (5), the required correction equation for the amplitude predistortion function to meet is

$$A\big(e.P(e)\big) = e\,, \quad \text{for } e.P(e) \leq e_{sat} \quad (19)$$

Expanding (19) by using (5) and solving it gives two solutions, and the smaller solution is taken as the required amplitude gain function, also when e >A_{max} it is impossible to obtain A(e.P(e))=e, so for this case P(e) is set to one. Thus, appropriate gain function is

$$P(e) = \begin{cases} \frac{\alpha_a - \sqrt{\alpha_a{}^2 - 4\beta_a e^2}}{2\beta_a e^2}, & e \leq A_{max} \\ 1, & e > A_{max} \end{cases} \quad (20)$$

Next the correction equation for the predistorter phase function is obtained from (6), which is given as

$$\Omega(r) + \phi(e.P(e)) = 0 \quad (21)$$

The expression for the predistorter phase distortion is

$$\Omega(e) = -\phi(e.P(e)) = -\frac{\alpha_\emptyset (e.P(e))^2}{1+\beta_\emptyset (e.P(e))^2} \quad (22)$$

IV. RESULTS AND DISCUSSIONS

The Fig.2 exhibits the output signal y(k) of the memory power amplifier when normalized 64-QAM signal, x(k), is given to its input for input back-off value of 5 dB. Similarly the output plots can be obtained for different back-off values. It is evident from the figure that output signal is spread around the input signal as a result of memory effect and nonlinearity of power amplifier. It will lead to larger bit error rate and adjacent channel interference during transmission.

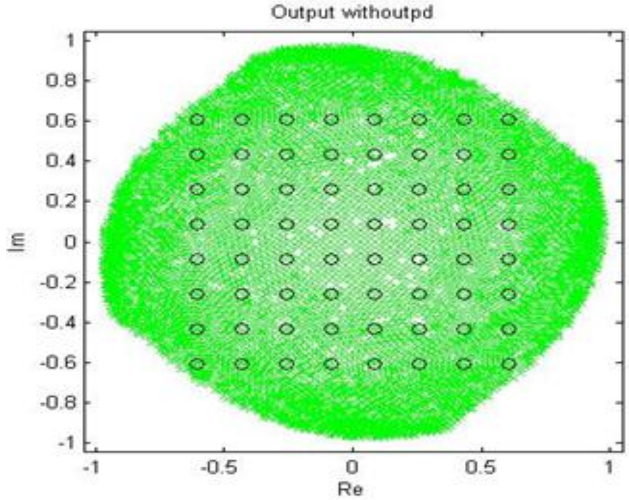

Fig2.Output from PA with IBO 5dB. 'x' represents output y(k) and 'o' represents input 64-QAM sognal x(k).

In this paper, identification process is done using both PSO and GA algorithms. The training data set taken contains 500 samples of normalized 64 QAM data. The noise with standard deviation 0.0 and 0.01 was added at output and identification was done for IBO=5, 10,15db. The results obtained were averaged over 100 runs. In PSO, instead of rand in (14), a vector containing N_α number of random number uniformly distributed between [0, 1] is used. The parameter vector for the estimated wiener power amplifier model obtained for each case is given by h^T = [0.777822614 0.155516821 0.076451606], t^T = [2.137008627 1.137645489 3.935456068 1.996214262] for PSO and h^T = [0.765382127 0.153215367 0.077231119], t^T = [2.176933106 1.205994222 4.010059489 2.058612345] for GA.

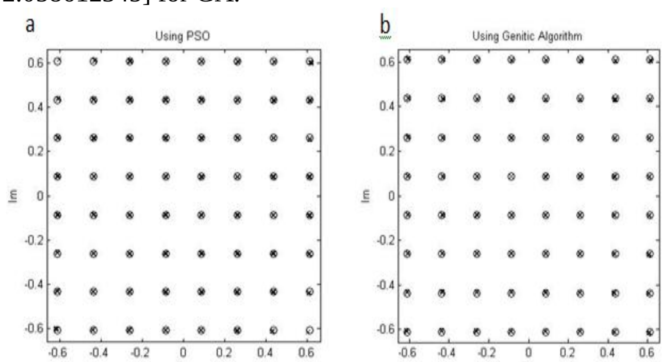

Fig3.(a) Input and Output using PSO(b) Input and output Using GA.

The linear filter of memory length of eight have selected for compensating memory effect of power amplifier model. Then solving expression (18) with help of estimated wiener model's linear filter coefficient, the resulting linear filter coefficients for each case is given as h^T = [1.285640173 -0.257049189 -0.074970543 0.040254684 -0.000679669 -0.003820711 0.000830712 0.000209443] for PSO and h^T =[1.306536911 -0.261544561 -0.079480117 0.042301686 -0.000448051 -0.004178773 0.000881724 0.000245156] for GA .

The constellation diagrams of output signal from the combined predistorter and wiener power amplifier model for each identification process is shown in Fig.3 for the IBO=5db (in fig.3, 'x' represents output y(k) and 'o' represents input 64-QAM signal x(k)). The plots shown are only for back-off value of 5db only. Similar plots can be obtained for different back-off values such as 10 db and15 db also. From fig.3, it can be seen that designed predistorters almost completely cancel out the nonlinear distortions and memory effects caused by the wiener memory high power amplifier model.

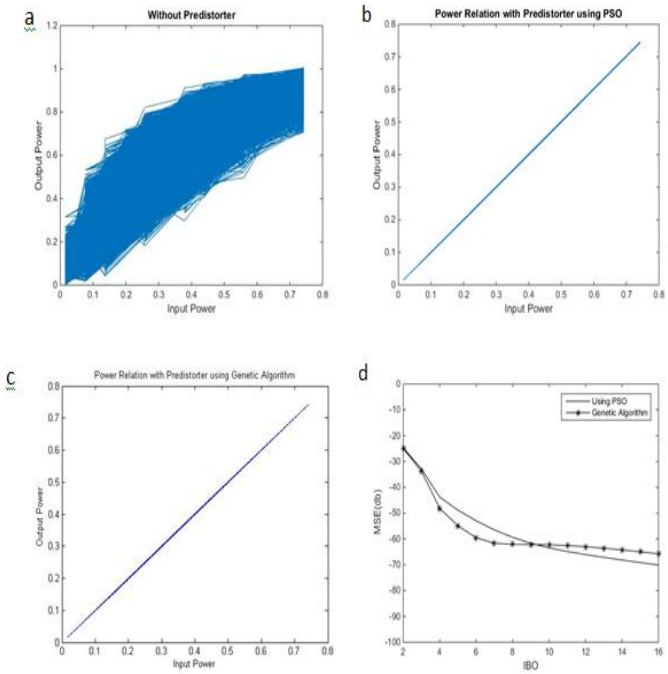

Fig4.(a) Without using predistorter; (b) Using predistorter (PSO); (c) Using predistorter (GA); (d) MSE vs IBO plot.

The relation between input power and output power obtained for the wiener power amplifier model without and with predistorter attached, with IBO=5db(similar plots can be obtained for 10db and 15 db also), when test data is applied to it is shown in Fig.4.(a), Fig.4.(b) and Fig.4.(c) It can be seen that due to nonlinearity Fig.4.(a) has curved form and because of memory effect its width has been became thicker. The figures with thin line are more effective in compensating memory effect than thicker line. From Fig.4.(b) and Fig.4.(c), it is clear that the designed predistorters perfectly compensated the nonlinearity. The proposed identification method using GA methods produced thin line than that using PSO. The performance of the designed predistorters were evaluated using following mean square error metric given below,

$$\mathrm{MSE} = 10\log_{10}\left(\frac{1}{K_{total}}\sum_{k=1}^{K_{total}} |x(k) - y(k)|^2\right) \quad (23)$$

Where K_{total} represents the total number of the test data, x(k) was the input signal and y(k) was the output from the combined predistorter and memory high power amplifier system. For calculating the effectiveness of predistorter K_{total} =20000 samples of normalized 64 QAM data were allowed to pass through the combination of predistorter and wiener power amplifier. The mean square error metric (MSE) was computed for each predistorters by noting input and output data. The obtained MSE for the predistorters are shown in table.1 as a function of IBO.

Table 1. MSE values for different IBO values.

IBO	PSO	GA
1	-18.95618605	-19.10427102
2	-24.7198172	-25.02965023
3	-32.89016651	-33.78366801
4	-43.81604546	-48.14430498
5	-48.85438404	-54.89832335
6	-52.96563348	-59.51414037
7	-56.47537939	-61.65228339
8	-59.37140006	-62.08907192
9	-61.65943319	-62.12817462
10	-63.43634097	-62.2555061
11	-64.85385755	-62.55108239
12	-66.0524343	-62.9983108
13	-67.13052069	-63.56682392
14	-68.14723463	-64.22965445
15	-69.13517427	-64.96550902
16	-70.11141742	-65.75802897

Fig.4.(d) depicts the MSE versus IBO plot for predistorters designed using corresponding estimated parameter vectors, where Wiener Power Amplifier is Implemented using hT =[0.7692 0.1538 0.0769] and tT =[2.1587 1.15 4.0 2.1].From Fig.4.(d) and Table.1. it is clear that predistorters designed with GA based identification method have greater reduction in MSE value than predistorter designed using PSO algorithm at lower IBO values. Also, it should be noted that as IBO value increases efficiency of power amplifier is reduced. Hence predistorter designed using GA can be considered as the best one that provides good linearization.

V. CONCLUSION

The predistorters designed using PSO and GA have effectively compensated various distortions caused by high power amplifier. The predistorter designed using GA dominates over the predistorter using PSO in terms of MSE for lower input back-off values. The MSE values can be extended by using some improved optimization algorithms which is expected to provide more good results and may lead to better linearization of the power amplifier.

VI. REFERENCE

[1] Sheng Chen, "An Efficient Predistorter Design for Compensating Nonlinear Memory High Power Amplifiers," IEEE Trans. Broadcasting, vol. 57, no. 4, pp. 2011.

[2] Biyi Lin, Yide Wang Bruno Feuvrie and Qingyun Dai, "A Novel Power Amplifier Linearization Technique based on Pre-distortion Principle and Wiener model," IJAST Vol. 22, September, 2010.

[3] Bipin P.R, P.V Rao," Predistortion of nonlinear power amplifier using ABC and PSO algorithms", IEEE Int. Conf.

Commn. And Signal Processing (ICCSP-2015), pp. 1505-1509, April 2015.

[4] J. Kennedy and R. C. Eberhart, “Particle swarm optimization,” in Proc. 1995 IEEE Int. Conf. Neural Networks, Perth, Australia, Nov. 27–Dec. 1 1995, pp. 1942–1948.

[5] Bipin P R, P.V Rao,”Artificial bee colony for pre-distortion of nonlinear power amplifiers,” IJEIR 2013.

[6] A. A. M. Saleh, “Frequency-independent and frequency-dependent nonlinear models of TWT amplifiers,” IEEE Trans. Communications, vol. COM-29, no. 11, pp. 1715–1720, Nov. 1981.

[7] S. Chen, X. Hong, B. L. Luk, and C. J. Harris, “Non-linear system identification using particle swarm optimisation tuned radial basis function models,” Int.J. Bio-Inspired Computation, vol. 1, no. 4, pp. 246–258, 2009.

[8] A. Ratnaweera and S. K. Halgamuge, “Self-organizing hierarchical particle swarm optimizer with time-varying acceleration coefficients,” IEEE Trans. Evolutionary Computation, vol. 8, no. 3, pp. 240–255, Jun.2004.